

The causal inference of cortical neural networks during music improvisations

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Abstract

In this paper, we present an EEG study of two music improvisation experiments. Professional musicians with high level of improvisation skills were asked to perform music either according to notes (composed music) or in improvisation. Each piece of music was performed in two different modes: strict mode and “let-go” mode. Synchronized EEG data was measured from both musicians and listeners. We used one of the most reliable causality measures: conditional mutual information from mixed embedding (MIME), to analyze directed correlations between different EEG channels, which was combined with network theory to construct both intra-brain and cross-brain neural networks. Differences were identified in intra-brain neural networks between composed music and improvisation and between strict mode and “let-go” mode. Particular brain regions such as frontal, parietal and temporal regions were found to play a key role in differentiating the brain activities between different playing conditions. By comparing the level of degree centralities in intra-brain neural networks, we found musicians responding differently to listeners when playing music in different conditions.

Key words: Music improvisation, EEG, MIME, Network.

Author summary

Introduction

Improvisation is an instantaneous creative behaviour that can be applied to different forms of art such as music and dance. In this paper, we study the brain mechanism involved in music improvisation. We refer to the performance according to notes as composed music, and the instantaneous creative performance as improvisation. In the performances, a piece of music was played either in a mechanical manner that is referred to strict mode, or in a more emotionally rich manner that is referred to “let-go” mode. In this study, the two different playing modes were applied to both composed music and improvisation.

Music improvisation as a creative behaviour is believed to have neuro-substrates in large brain regions. If we could find these brain regions, we may then be able to use neuroscientific approaches to improve the quality of music performance. To understand the mechanisms of music improvisation, we investigated various kinds of time series causality measures and finally used the conditional mutual information from mixed embedding (MIME, a time domain direct causality measure developed by I. Vlachos and D. Kugiumtzis [56]), which was identified as the optimal causality measure to analyze our EEG data. In this paper, we present results on intra-brain and cross-brain neural networks, from which we managed to identify the neural differences between composed music and improvisation, between strict mode and “let-go” mode and between musicians and listeners.

Music improvisation has long been studied by neuroscientists and mathematicians using various approaches. In recent decades, scientists have started using fMRI, PET, and EEG for brain scanning. O. D. Manzano and F. Ullen used fMRI scanning, with a 2×2 factorial experiment design to study melodic

and rhythmic improvisation [40], [41]. They found that the dorsal premotor cortex (PMD) is mainly responsible for melodic improvisation, whilst the pre-supplementary motor area (pre-SMA) is related to rhythmic improvisation [40], [41]. A. L. Berkowitz and D. Ansari [13] used fMRI to study expertise-related differences in brain activity between musicians and non-musicians during improvisation. They discovered that musicians have right temporoparietal junction (rTPJ) deactivation during music improvisation, whilst non-musicians showed no activity change in this region [13]. Moreover, C. Babiloni et al. [7] studied frequency filtered EEG data obtained from professional saxophonists during music performances. They found that during resting state dominant EEG power density values were observed in the alpha band (8 – 12Hz) in the posterior cortex. These alpha power values were then enhanced within narrow high-frequency bands during the music performance [7]. Other relevant brain studies include, e.g. the EEG phase synchrony analysis by J. Bhattacharya and H. Petsche [15], jazz improvisation studies using fMRI by C. J. Limb and A. R. Braun [36], PET studies of melody and sentence generation by S. Brown, M. J. Martinez and L. M. Parsons [18], and the fMRI study of pseudorandom motor and cognitive tasks by S. L. Bengtsson, M. Csikszentmihalyi and F. Ullen [11].

Amongst the many mathematical tools used, the two most relevant tools to our research are: standardized Low Resolution Brain Electromagnetic Tomography (sLORETA, [45]) and Analysis of Variance (ANOVA, [42], [50]). sLORETA is a method that is used to localise, identify and visualise the EEG point sources in the brain [45]. ANOVA is a measure that evaluates the group correlations between data channels [42], [50]. Both of these methods have a drawback in that they cannot detect directed interactions between brain regions. In spite of this limitation, both methods have been used in music improvisation studies. For instance, the music improvisation study on trained pianists by A. L. Berkowitz and D. Ansari, which demonstrated that both rhythmic and melodic motor sequence creation modulate activity in a network of brain regions comprised of the dorsal premotor cortex, the rostral cingulate zone of the anterior cingulate cortex and the inferior frontal gyrus [14]. D. Dolan, et al. undertook an EEG study of music improvisation using sLORETA [22]. This analysis used some of the same data collections that we have used in this paper, these being the EEG measurements in the trio ensemble. sLORETA suggested some similar results to those we found from our MIME analysis regarding the level of brain activities and the differences in the frontal and temporal activities between music types and playing modes. However, their analysis did not address cross-correlations between different EEG channels. In this paper, we complement the EEG analysis by using MIME causality measure and network theory.

In our study, we explored the three most popular measures: nonlinear measures such as transfer entropy (TE, [51]), MIME ([56]) and a linear direct method: partial directed coherence (PDC, [52], [53]), amongst other causality measures. In another publication, we will describe the comparison between these measures in detail. Here, we simply acknowledge that TE produces causality results with unsatisfactory resolution, whilst PDC sometimes returns false or unreliable causalities due to autoregressive model fitting limitations. MIME, on the other hand, appears to generate reliable and robust results with satisfactory resolution. Hence, here we only report the MIME estimates of the information flow between musicians and listeners and the dependence of causalities on experimental conditions.

Our study

In this paper, we discuss two experiments regarding the effects of music performance in different types of music (composed music and improvisation) and different playing modes (strict mode and “let-go” mode). Our main interest is to identify the direction of neural information flow between EEG channels using the MIME causality measure. It is noteworthy that our emphasis was on making the experimental environment as close to that of a real concert performances as possible. This emphasis was especially made in the second experiment, which presents a more extensive experiment.

The experiments were conducted at GuildHall School of Music and Drama, on 20.06.2010 and on 31.03.2012. EEG data was collected by Björn Crüts and his team (BrainMarker Corp.) from musicians and listeners during the music performances. In the first experiment, international concert pianist David Dolan played four short pieces:

Test 1: Schubert-Impromptu in G flat major Op. 90 No. 3, neutral mode, uninvolved

Test 2: Schubert-Impromptu in G flat major Op. 90 No. 3, fully involved

Test 3: Improvisation, polyphonic, intellectual exercise

Test 4: Improvisation, polyphonic, emotional letting go.

The audience consists of one listener. Both participants were connected to synchronized EEG amplifiers with 8 electrodes (P4, T8, C4, F4, F3, C3, T7, P3) sampled at 250Hz.

In the second experiment, music was performed by Trio Anima. The trio consists of three highly acclaimed musicians: Drew Balch (violinist), Matthew Featherstone (flutist) and Anneke Hodnett (harpist). Two listeners participated in the EEG measurements, but due to technical issues, one EEG machine connecting to a listener turned out to be unsynchronized with the other four machines. Therefore, only the listener with synchronized EEG data was used for cross-brain network analysis, intra-brain analysis uses the data from both listeners. The EEG data in this experiment was measured from 10 electrode sites, including two occipital sites O1 and O2. The music was performed in the following order:

A. Ibert [duration: 3'30"]: 1. strict & 2. "let-go"

B. Telemann [duration: 2']: 1. "let-go" & 2. strict

C. Improvisation: 1. "let-go" & 2. strict

D. Ravel [duration: 2'50"]: 1. strict & 2. "let-go"

E. Improvisation: 1. strict & 2. "let-go"

Pieces A, B, and D are composed music, while pieces C and E were entirely improvised by the trio. Both composed music and improvisation were played in two modes: strict mode and "let-go" mode.

According to Dr. David Dolan, the differences between composed music and improvisation occur mainly in the overall manner of the music performance. Improvisation contains more coherent and long-term structural lines, shared by all members of the ensemble. The short-term beats are freer and uneven, but the deep, longer-term pulse is extremely stable in the "let-go" mode. In performances of composed music, the gestures seem to be shorter and more rigid (even in quick repetitive phrases). There is less room for spontaneity and audience find themselves less surprised. This is perhaps the reason behind the results of psychological tests, which showed that audiences found that improvisation is more emotionally engaging as well as musically interesting [22]. Extra notes were added spontaneously by the freer distribution of time over gestures, which leans more significantly on structural key moments. Another important characteristic of improvisation, is that the risk-taking and support are provided spontaneously by the members of the ensembles to each other. This is probably a consequence of the higher level of active listening that took place during the improvisation. One may hence expect that when playing non-composed music musicians are prevented from entering into 'autopilot mode' as they need to listen attentively during the improvisation, because the unexpected was to come.

Given the above descriptions of mental and behavioral differences between different types of music performances and playing modes, we aim to find their neural substrates based on the direction of neural information flows and the topological structure of neural networks. Previous research considered either unique EEG point sources or symmetric correlations between different brain regions. Few studies have been undertaken on intra-brain or cross-brain neural networks constructed from the theoretic information flow between different EEG channels. In this paper, we present our cross-neuron causality analysis between EEG channels both for intra-brain and cross-brain, by means of the conditional mutual information from mixed embedding (MIME, [56]). As mentioned before, the reason for using MIME is that it generates plausible causalities. MIME has been tested on real EEG data from reading experiments (refer to Subsection : Causality verification of MIME), in which it identifies the correct cross-brain causality from reader to listener. This test convince us that MIME does not generate false causalities. Hence, we believe that the theoretic information flow identified by MIME is reliable. Furthermore, we used network theory to construct intra-brain neural networks, in which the nodes are the 4×10 EEG electrodes and the edges are the directed weights generated by MIME. We analysed the topological structure of the networks and the dependence of these networks on music types and playing modes.

Results

We have used MIME to analyse the causalities between EEG channels of the music experiments. These MIME causalities were then used to construct both intra-brain neural networks and cross-brain coordination networks between musicians and listeners. Moreover, to analyse the importance of large brain regions, we further used degree centralities to analyse the intra-brain neural networks.

Intra-brain neural information flow

In our analysis, each brain is considered as a network composed of cortical regions joint by neural information flows. We used the directed MIME causalities to construct the intra-brain neural networks. A link is drawn in the neural network if the causality value is positive in this direction. Before we draw the links, we first average the MIME causalities over time windows to produce an overall average.

In the first experiment, the pianist and listener each has two networks, one for composed music and the other for improvisation, which are shown in Figures 1 (pianist) and 2 (listener). In these networks, neural difference was observed between composed music and improvisation in the distribution of neural information flows. In the networks of pianist (Figure 1), the distribution of neural information flows expands from the back of the brain to the entire brain when composed music changes to improvisation. A similar process was observed for the listener, in which the distribution of neural information flows expands from the right brain to the entire brain when composed music changes to improvisation (Figure 2).

In the second experiment, strict mode and “let-go” mode were added as extra conditions. To compare the differences between pairwise conditions, we extract the contrasts of MIME causalities between composed music and improvisation and between strict mode and “let-go” mode. Since the contrast values oscillate in time, we used a significant thresholding test to identify significant values in the following way. We first define a radius $R = (Max_{contrast} - Min_{contrast})/2$ as half of the difference between the maximum and minimum contrasts, then a significant threshold was defined as half of the radius $T = R/2$. Only values that lie outside the interval $(-T, T)$ were considered as significant, e.g. the $(C3, T7)$ -th lattice

($C3 \rightarrow T7$) with contrast value of 0.1 (maximum value in the colorbar) in the left panel of Figure 3.

In comparison between the conditions, we found that composed music has overall larger intra-brain causality values than improvisation, which implies more links for “composed music > improvisation” than for “composed music < improvisation” in the networks of Figure 4. In this figure, the left panel is for musicians and the right is for listeners. For musicians, information flows that are significant in composed music are from both left and right central regions to the left temporal region ($C3, C4 \rightarrow T7$) and from the right frontal region to the right occipital region ($F4 \rightarrow O2$). As to the listeners, information flows that are significant in composed music are from the left frontal and left parietal regions break into two brunches, one is to the left temporal region ($F3, P3 \rightarrow T7$), while the other is to the right frontal region via the right central ($F3, P3 \rightarrow F4$, or $F3, P3 \rightarrow C4$ and $C4 \rightarrow F4$) and right temporal regions ($P3 \rightarrow T8$ and $T8 \rightarrow F4$, or $F3, P3 \rightarrow C4$ and $C4 \rightarrow T8$ and $T8 \rightarrow F4$). The left frontal ($F3$) and left parietal ($P3$) regions acted as the main sources of information flows, whilst the left temporal ($T7$) and right front ($F4$) regions are the main sinks. The right central ($C4$) and right temporal ($T8$) regions played as transit hubs. The listeners also have significant information flows in improvisation (“composed music < improvisation”), which are from the right frontal region to the left frontal ($F4 \rightarrow F3$) and right temporal regions ($F4 \rightarrow T8$) and from the left central to the left frontal region ($C3 \rightarrow F3$), which are inverse directions to the flows in composed music (“composed music > improvisation”).

The network structures are more complicated for strict mode and “let-go” mode (Figure 5). For musicians (left panel), information flows that are significant in strict mode are from the left frontal region to the left and right central regions ($F3 \rightarrow C3, C4$) and to the left occipital ($F3 \rightarrow O1$) and the right temporal ($F3 \rightarrow T8$) regions, from the right frontal and left central regions to the left temporal region ($F4, C3 \rightarrow T7$) and from the right parietal region to the left central ($P4 \rightarrow C3$), right occipital ($P4 \rightarrow O2$) and right temporal ($P4 \rightarrow T8$) regions. Here, we see that the left frontal region ($F3$) and the right parietal ($P4$) region are key to musicians playing in strict mode (“strict > let-go”). However, in the same intra-brain neural network for musicians, information flows that are significant in “let-go” mode are from the right frontal region to left occipital region ($F4 \rightarrow O1$) and from the right parietal region to left temporal region ($P4 \rightarrow T7$). For listeners, there is a clear difference in the distribution of neural information flows. Information flows significant in strict mode (“strict mode > let-go mode”) are from the left parietal to the left frontal ($P3 \rightarrow F3$) and left temporal regions ($P3 \rightarrow T7$), from the right temporal region to the left temporal region ($T8 \rightarrow T7$) and from the right central region to the right frontal region ($C4 \rightarrow F4$), whereas information flows significant in “let-go” mode (“strict mode < let-go mode”) are from the left and right frontal regions to the right central ($F3, F4 \rightarrow C4$) and right temporal regions ($F3, F4 \rightarrow T8$) and from the left central region via the left temporal region to the right central region ($C3 \rightarrow T7 \rightarrow C4$). Strict mode has a trend of flows from the back to the front of the brain, whilst “let-go” mode has a trend in the inverse direction from the front to the back of the brain.

Degree centrality analysis

In the intra-brain neural networks for musicians and listeners, different brain regions play different roles. In order to differentiate the level of importance of large brain regions during different types of performances, we undertook a degree centrality analysis on the intra-brain neural networks. Since the neural networks are directed networks, we calculate both the in-degree centralities and out-degree centralities. By taking averages of the degree centralities over musicians and over listeners, we found that musicians have different trends of degree centralities to listeners for every pair of experimental conditions.

For the comparison between composed music and improvisation, we calculated the contrasts between the degrees in composed music and the degrees in improvisation (the Figure 6). We found that musicians

have larger (both in and out) degrees in improvisation than in composed music, but listeners have larger (in and out) degrees in composed music than in improvisation. A similar contrast was found between the degrees in strict mode and the degrees in “let-go” mode, we see that musicians have larger (in and out) degrees in strict mode than in “let-go” mode. Listeners, on the contrary, have larger degrees in “let-go” mode than in strict mode (Figure 7). In all cases, musicians and listeners exhibit opposite trends for the degree centrality. In this analysis, a larger degree implies more connectivities and hence higher integration between brain regions.

Cross-brain networks

It was reported by P. Vuust in a study of jazz performances [57], [58], the jazz musicians coordinate with each other by modulating their rhythm during ensemble performances. In our experiments, the three members of the trio had to interact with each other during the performances. To investigate their coordination, we conducted a cross-brain analysis including all participants. In our analysis, we calculated the averages of the cross-brain causalities, which result in a single real number assigned to each direction. A cross-brain link exists from one brain to another in the cross-brain networks, if the single real number (i.e. the average over all possible electrode pairings between the two brains, see Figure 8) is significantly larger in this direction than in the inverse direction. For instance in Figure 9, the cross-brain causality averages of flutist→listener and listener→flutist were plotted against time windows. In this figure, flutist→listener has clearly larger averages than listener→flutist, hence a directed link exists from the flutist to the listener.

In the cross-brain network of the first experiment, there are two nodes, one for pianist and one for listener. The unique direction of cross-brain link is drawn from pianist→listener (average weights: $A_{P \rightarrow L} = 0.6554 \cdot 10^{-4} > A_{L \rightarrow P} = 0.1352 \cdot 10^{-4}$). In the cross-brain network of the second experiment, there are four nodes, three for musicians and one for listener (the other listener is unsynchronised to the rest and was neglected in this analysis), the direction of cross-brain links are from all three musicians to the listener: [flutist, harpist, violinist]→listener (average weights: $A_{F \rightarrow L} = 0.1647 > A_{L \rightarrow F} = 0.0304$, $A_{H \rightarrow L} = 0.2002 > A_{L \rightarrow H} = 0.0053$ and $A_{V \rightarrow L} = 0.1901 > A_{L \rightarrow V} = 0.0392$), from the harpist to the flutist and violinist: harpist→[flutist, violinist] (average weights: $A_{H \rightarrow F} = 0.0680 > A_{F \rightarrow H} = 0.0033$ and $A_{H \rightarrow V} = 0.0945 > A_{V \rightarrow H} = 0.0097$) and the flutist pingsongs with the violinist: flutist↔violinist ($A_{F \rightarrow V} = 0.0509 > A_{V \rightarrow F} = 0.0515$, the average values are high in both directions, when smeared along time windows, the direction flips around a couple of times). This network structure is robust for all performances in the second experiment.

Discussion and summary

We have constructed both intra-brain and cross-brain networks for musicians and listeners during music performance, in which the structure of intra-brain neural networks depends on different experimental conditions, whilst the cross-brain networks are unchanged when experimental conditions altered. In our analysis, improvisation tends to trigger more spread out intra-brain network structures than composed music. Composed music and improvisation, strict mode and “let-go” mode can also be distinguished by the sink and source activity in frontal, parietal and temporal regions (similar to the results obtained by sLORETA analysis for the same data set [22], [21]), the direction of neural information flows, as well as the level of importance or degree of cross-neuron integration for large brain regions. Musicians have been found to have opposite trends to listeners in the overall centrality measure for every pair of conditions. Musicians have overall larger degree centralities in improvisation than in composed music and in strict mode than in “let-go” mode, which maybe because musicians need more brain powers to improvise (i.e.

to create melodies and rhythms instantaneously) and need more brain attention to perform in strict mode. However, listeners have larger degree centralities in composed music than in improvisation and in “let-go” mode than in strict mode, which may be because they found the music that was played according to notes is more familiar than improvisation and the music performed in “let-go” mode is more beautiful than the music played in strict mode (according to questionnaire statistics provided in [22] on music improvisation approaches, which uses part of the same data as we did in this paper).

These findings demonstrate that by use of network analysis based on the MIME causality measure we are able to detect differences in the state of the brain, for musicians and for listeners, associated with the performance of music in either strict mode or “let-go” mode. Similar differences can be detected for the performance of composed music or freely improvised music. This analysis provides a potential tool which can give us more insight into intra-brain and inter-brain information flows. Hence, it is very promising for quantifying and evaluating group processes such as music performances. This method of analysis can be applied to more general datasets, such as financial data and neuroscience time series.

In intra-brain neural networks, we found improvisation exhibits more extensive neural networks than composed music. This may be because either performing or listening to improvisations demands a more widespread functional integration between large brain regions. In comparison between composed music and improvisation, we found the causality values are generally larger in composed music than in improvisation, this is especially the case for the listeners. The analysis also shows that the frontal regions play an important role in intra-brain neural networks, which were the key region that distinguish composed music from improvisation and strict mode from “let-go” mode. The information flows start and terminate separately in left frontal and right frontal regions, the direction of information flow reversed when the composed music changes to improvisation and strict mode changes to “let-go” mode. Amongst the many large brain regions, the central regions were observed as transit hubs for the neural information flow, whilst the temporal and parietal regions also played important roles in distinguishing the pairwise conditions.

In the centrality analysis, we used the degree centrality to analyse the importance of large brain regions, because it is simple to calculate and it is the most suitable centrality measure for directed networks. Other centrality measures such as eigenvector centrality and Katz centrality often don’t work well for directed networks and their computation are more complicated than degree centrality.

Finally, the cross-brain networks we constructed for musicians and listeners, provides sensible directions of interaction amongst musicians and between musicians and listeners. In the cross-brain network, the musicians are pointing to listeners, which seems reasonable since the musicians are communicating *to* the listeners. The harpist was frequently found to lead the flutist and the violinist, this may be because the harp instrument provides the chord structure which were received by flutist and violinist.

Methods

In our analysis, we used the MIME software developed by I. Vlachos and D. Kugiumtzis, et al. [56] to calculate the causalities between EEG data channels. MIME is a time domain method used to quantify nonlinear causal effects by using conditional mutual information rates. It uses a progressive scheme to select mixed embedding vectors which can maximize the conditional mutual information between future and past embedding vectors [56]. For a K-dimensional stationary vector process $X_n = [x_{1,n}, \dots, x_{K,n}]$, to calculate the causality from x_j to x_i , the MIME starts a future vector containing the future of the

driven variable (x_i)

$$v_F = (x_{i,n+1}, x_{i,n+2}, \dots, x_{i,n+T_i}),$$

a uniform state-space embedding vector consists of the lagged values from both driving (x_j) and driven (x_i) variables

$$\mathbf{B} = (x_{i,n}, x_{i,n-1}, \dots, x_{i,n-L_i}, x_{j,n}, \dots, x_{j,n-L_j}),$$

and an empty vector $\mathbf{b}_0 = \emptyset$ defined as the initial selected non-uniform state-space embedding vector, where T_i is the time horizon (prediction step) of x_i , L_i, L_j are the maximum time lags for x_i and x_j , respectively. The progressive skeme then runs to select elements in \mathbf{B} that can be add to \mathbf{b}_0 . At a s -th iterative circle, MIME seeks element in \mathbf{B} which satisfies the maximum criterion

$$I : \max_{x_s} \{I(v_F; x_s | \mathbf{b}_{s-1})\}. \quad (1)$$

If an element in \mathbf{B} satisfies the maximum criterion, it is then added to the selected embedding vector \mathbf{b}_{s-1} from last step to generate \mathbf{b}_s for this step. The progressive skeme stops at the s -th iterative circle and uses \mathbf{b}_{s-1} as the final embedding vector when the stopping criterion

$$I(x_F; \mathbf{b}_{s-1}) / I(x_F; \mathbf{b}_s) > A, \quad (2)$$

is satisfied. Here, $A \in (0, 1)$ is a threshold close to 1 with empirical value $A = 0.95$ gives the optimum results. The software uses $A = 0.95$ as the default.

After termination of the progressive skeme, MIME measures the causal effect from one variable $x_{j,n}$ to another $x_{i,n}$ ($i, j = 1, \dots, K, i \neq j$) by calculating the ratio of the conditional mutual information, i.e.

$$R_{x_j \rightarrow x_i} = 1 - \frac{I(\mathbf{v}_F; \mathbf{b}_{s-1}^i)}{I(\mathbf{v}_F; \mathbf{b}_{s-1})} = \frac{I(\mathbf{v}_F; \mathbf{b}_{s-1}^j | \mathbf{b}_{s-1}^i)}{I(\mathbf{v}_F; \mathbf{b}_{s-1})}, \quad (3)$$

where $\mathbf{b}_{s-1} = [\mathbf{b}_{s-1}^i, \mathbf{b}_{s-1}^j]$ is the final selected non-uniform state-space embedding vector when the progressive skeme terminates, \mathbf{b}_{s-1}^i and \mathbf{b}_{s-1}^j are its i th and j th components, respectively.

To analyse cross-brain information flows, synchronized EEG data from different brains was binded together in pairwise, e.g. the EEG data from pianist was bined with listener's to form an argmented data file with doubled data channels. These augmented data files were then sliced by moving time windows which have constant window size of $\Delta T_1 = 4s$ ($f_{1,sample} = 250\text{Hz}$) for the first experiment and $\Delta T_2 = 10s$ ($f_{2,sample} = 100\text{Hz}$) for the second experiment. These time windowed data files were used as the final input to the MIME software.

The MIME software outputs sequences of square matrices, which contain both intra-brain and cross-brain causalities. These matrices are of size 16×16 (20×20) for the first (second) experiment, which constitute of two 8×8 (10×10) diagonal submatrices for intra-brain causalities and two 8×8 (10×10) off-diagonal submatrices for cross-brain causalities. The diagonal submatrices (intra-brain) were averaged over time windows to construct intra-brain neural networks. To calculate degree centralities, we threshold to extract a binary matrix. Then, we transpose the diagonal submatrices into directed adjacency matrix of intra-brain neural networks, then use these directed adjacency matrices to compute the degrees. The off-diagonal submatrices (cross-brain) were used to construct cross-brain networks by averaging the cross-brain causalities in each direction, and comparing the averages between brain pairs. A cross-brain link is drawn from one brain to another, if the average causality value is clearly larger from this brain to the other than in its reverse direction. If the average values have equivalent magnitudes in both directions, the cross-brain causality cancel each other and we will not draw any link between this pair of brains.

Causality verification of MIME

We use MIME for our EEG analysis, because we found it is more reliable than other measures we have tried such as TE ([51]) and PDC ([52], [53]). MIME has been checked extensively on model data [56] and was found to represent correctly all directional interdependencies. It was also tested on EEG data for epilepsy patient [56], where it was found to produce reasonable results. To our knowledge, MIME has not yet been used in cross-channel EEG analysis on music improvisation. To verify the directionality of our MIME results, we designed two reading experiments, aim to check the directional inference of MIME.

In the reading experiment, we have one reader and one listener, both of which are healthy normal people. The reader’s task is to read a short story to the listener, while the listener’s task is to listen to the story carefully and try to imagine the scene described in the story. When the first reading is finished, after a short break, they were asked to swap roles to repeat the reading test again. The stories were new to both reader and listener, and they were not allowed to face each other during the tests, in order to eliminate visual effects. Synchronised EEG data was measured from 10 electrodes (P4, O2, T8, C4, F4, F3, C3, T7, P3, O1) at 100Hz sampling frequency for both reader and listener during the reading processes. The whole experiment was repeated once on another pair of subjects to avoid fortuity.

Results show that MIME is reliable in this EEG analysis, it does not produce false positives on directional inference. In the first reading experiment, it gives the average (cross-brain) causalities $W_{reader \rightarrow listener} = 0.0523$ and $W_{listener \rightarrow reader} = 0.0034$ in one test, but $W_{reader \rightarrow listener} = 0.0192$ and $W_{listener \rightarrow reader} = 0.0215$ in the other case. In the second reading experiment, it gives $W_{reader \rightarrow listener} = 0.5971$ and $W_{listener \rightarrow reader} = 0.0012$ in one case, but $W_{reader \rightarrow listener} = 0.1008$ and $W_{listener \rightarrow reader} = 0.1035$ in the other case. For both experiments, we could draw a link from the reader to the listener, rather than the inverse direction, because the causality average is clearly greater from reader to listener than from listener to reader in one case, even though in the other case the causality averages have equivalent strength, thus the directions cancel each other (in which case we will not draw any links between reader and listener). We note that between each pair of two brains, we draw at most one directed link given by dominant causality average.

We altered the parameters of MIME, e.g. the time horizon (prediction step) $T = 1, 2, 3$ and the maximum embedding dimension (time lags) $L_{max} = 3, 4, 5$ under restriction that $T < L_{max}$ [56], the directional results were the same. This means that the causality directions are independent of parameter choice. Our conclusion is that MIME may fail to pickup causal links, as when we find nearly equal strength in both directions between reader and listener. However, if MIME detects a causal direction we have reason to believe the result is reliable.

Selection of causality measures

There are a couple of reasons for us to use MIME amongst many other causality measures in our EEG analysis. Firstly, we have compared our EEG analysis using the three popular measures: MIME [52], [53], PDC and TE [51], in which MIME generates the most reliable results. PDC is a linear method which relies on linear autoregressive models. In real EEG data analysis, PDC presents larger amount of presumably false causalities from listeners to musicians rather than from musicians to listeners. TE is a nonlinear method, which is supposed to be better than PDC in analysing nonlinear time series. However, due to computational restrictions on embedding dimensions, TE can not reach its ideal embedding dimension, thus can not produce satisfactory directional results. In TE’s analysis, we found it generates balanced causalities between every pair of brains, which can not be used in analysing cross-brain network structures. A small increment in embedding dimension costs incredible longer computation times.

The linearity and computation issues were addressed by MIME, which can produce reliable directional results on model free data consuming reasonable computation times [56]. As has been tested on various theoretical maps, MIME reproduces all directional results correctly [56]. In order to test the reliability of MIME on real EEG data, we undertook two reading experiments (refer to Section: Causality verification of MIME), which convincingly indicate that MIME doesn't present false positives in analysing causal effects between EEG channels.

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Figure Legends

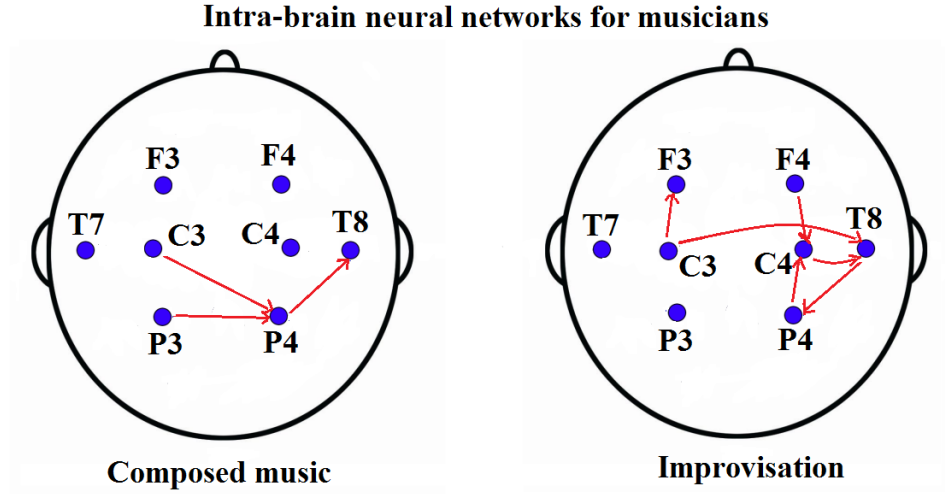


Figure 1. Pianist's intra-brain neural networks in the first experiment. The left panel is for composed music, while the right panel is for improvisation. The intra-brain neural networks composed of 8 large brain regions which are represented by the 8 electrodes: F3, F4, C3, C4, T7, T8, P3, P4. The capital letters are initials of the cortical regions, F: frontal cortex (attention and executive control), C: central cortex (sensory and motor function), T: temporal cortex (processing of language and sounds), P: parietal cortex (perception, multisensory integration). Odd number stands for the left brain, while even number represents the right brain. In composed music (left panel), the intra-brain neural network contains information flows: $P4 \rightarrow T8$, $C3 \rightarrow P4$, $P3 \rightarrow P4$, while in improvisation (right panel), the network consists of information flows: $P4 \rightarrow T8$, $C3 \rightarrow F3$, $F4 \rightarrow C4$, $C3 \rightarrow T8$, $C4 \rightarrow T8$, $P4 \rightarrow C4$, in which $P4 \rightarrow T8$ is the common link between the two networks. We use these two networks to compare the neural differences between composed music (mechanical music performances according to notes) and improvisation (instant creative performance of music) for pianist's brain, in which an expansion of neural information flows from the back brain to the entire brain was observed, when composed music changed to improvisation.

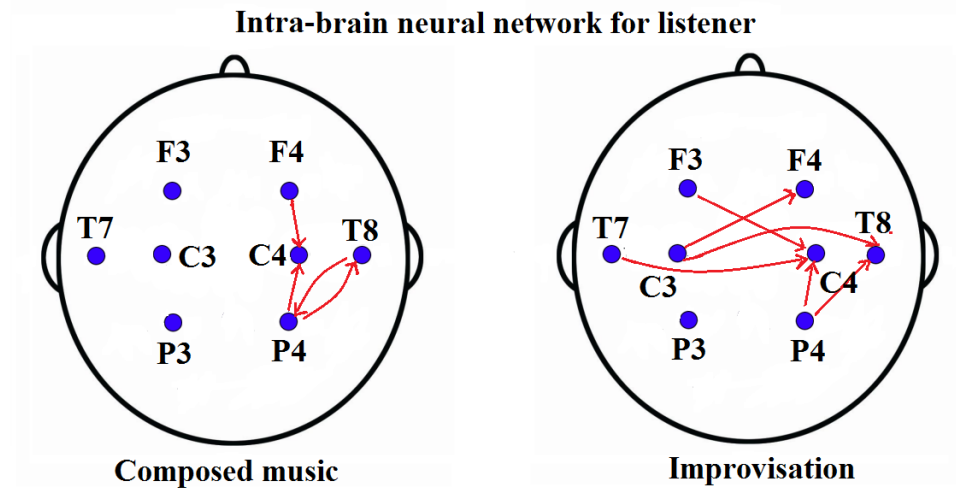


Figure 2. Listener's intra-brain neural networks in the first experiment. The left panel is for composed music, while the right panel is for improvisation. The intra-brain neural networks composed of 8 large brain regions which are represented by the 8 electrodes: F3, F4, C3, C4, T7, T8, P3, P4. The capital letters are initials of the cortical regions, F: frontal cortex (attention and executive control), C: central cortex (sensory and motor function), T: temporal cortex (processing of language and sounds), P: parietal cortex (perception, multisensory integration). Odd number stands for the left brain, while even number represents the right brain. In composed music (left panel), the intra-brain neural network contains information flows: $P4 \rightarrow C4$, $P4 \rightarrow T8$, $T8 \rightarrow P4$, $F4 \rightarrow C4$, while in improvisation (right panel), the network consists of information flows: $P4 \rightarrow C4$, $P4 \rightarrow T8$, $F3 \rightarrow C4$, $C3 \rightarrow F4$, $C3 \rightarrow T8$, $T7 \rightarrow C4$, in which $P4 \rightarrow C4$, $P4 \rightarrow T8$ are the common links between the two networks. We use these two networks to compare the neural differences between composed music (mechanical music performances according to notes) and improvisation (instant creative performance of music) for listener's brain, in which an expansion of neural information flows from the right brain to the entire brain was observed, when composed music changed to improvisation.

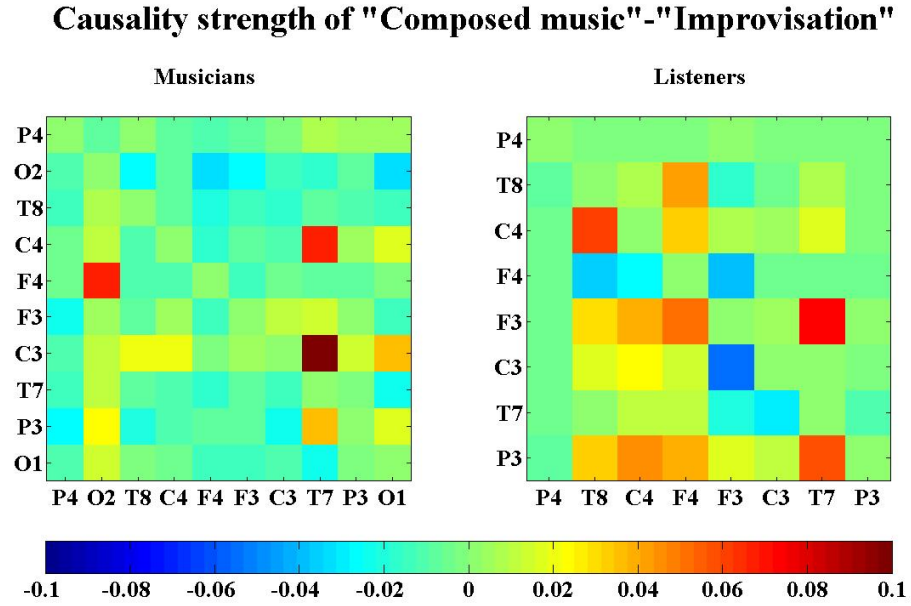


Figure 3. Colour-map of the causality contrasts between composed music and improvisation. In this figure, the 10×10 lattices represent the contrasts of intra-brain causalities between composed music and improvisation, in which the colour scaled between -0.1 and 0.1 reflects the magnitudes of contrasts. The direction of causality across the 10 EEG channels are indicated from rows to columns. For instance, the (C3,T7)-th lattice on the left graph indicates the contrast of causality from C3 to T7. The left panel is the average for musicians, while the right panel is the average for listeners. The contrast intra-brain neural networks between composed music and improvisation (Figure 4) were drawn from this figure.

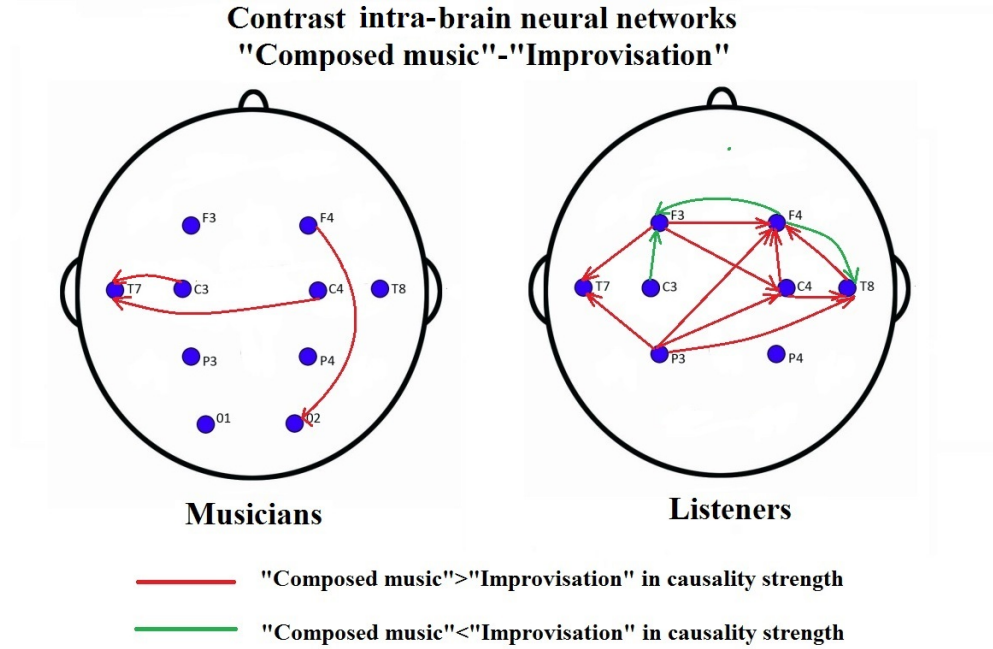


Figure 4. The contrast intra-brain neural networks between composed music and improvisation in the second experiment. These contrast neural networks were drawn from Figure 3 (the color map of the causality contrast). The causality contrasts were calculated by taking the differences of the MIME causalities between composed music and improvisation. A link is drawn in this network if the causality contrast is significant according to a thresholding test. For each matrix of contrast causalities, we define a radius R_c as half of the differences between the maximum C_{max} and minimum C_{min} of the contrast values, i.e. $R_c = (C_{max} - C_{min})/2$. The threshold is then set as half of the radius: $T_c = R_c/2$, where we consider the contrast values that lie outside the interval $(-T_c, T_c)$ as significant and hence were drawn as links in these graphs. Here, the 10 nodes were represented by the 10 electrodes: F3 & F4 (frontal cortex: attention and executive control), C3 & C4 (central cortex: sensory and motor function), T7 & T8 (temporal cortex: processing of language and sounds), P3 & P4 (parietal cortex: perception, multisensory integration), and O1 & O2 (occipital cortex: visual processing). Odd number stands for left brain, while even number represents the right brain. Here, we found that the MIME causalities are stronger during composed music than during improvisation. The red links show the information flows that are significant in composed music, for musicians (left panel) we have: $C3 \rightarrow T8$, $C4 \rightarrow T7$, $F4 \rightarrow O2$, while for listeners (right panel) we have: $F3 \rightarrow [F4, C4, T7]$, $P3 \rightarrow [F4, C4, T8]$, $C4 \rightarrow [F4, T8]$, $T8 \rightarrow F4$. The green links indicate the information flows that are significant in improvisation, this only happens for listeners (right panel): $F4 \rightarrow [F3, T8]$, $C3 \rightarrow F3$. We see in listeners' brains (right panel) in composed music, the left frontal and left parietal regions act as the main sources of information flows, whilst the right frontal region plays as the main sink of information flows, the direction of information flow reverses when composed music changes to improvisation.

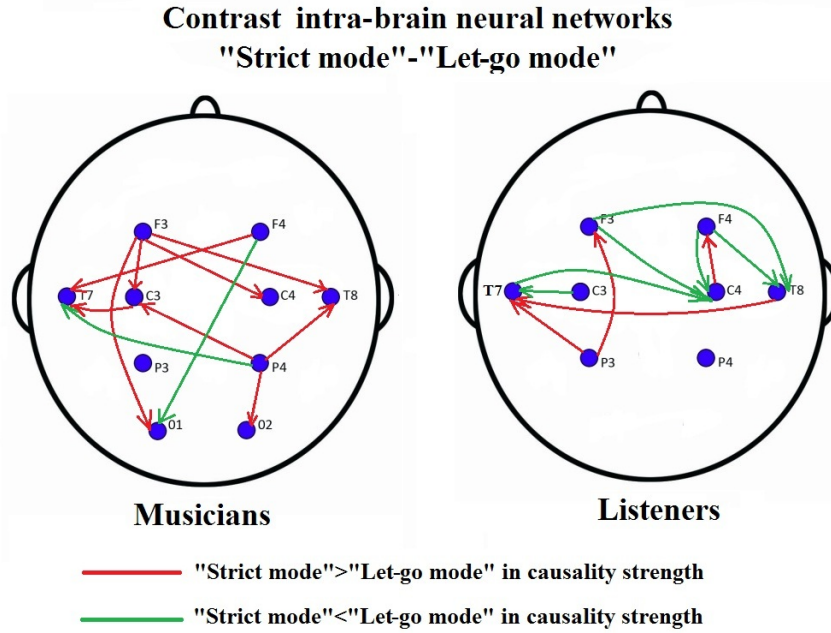


Figure 5. The contrast intra-brain neural networks between strict mode and let-go mode in the second experiment. The causality contrasts were calculated by taking the difference of MIME causalities between strict mode and “let-go” mode. A link is drawn in the networks if the causality contrast is significant according to a thresholding test, the same as used in Figure 4. In these networks, the 10 nodes were represented by the 10 electrodes: F3 & F4 (frontal cortex: attention and executive control), C3 & C4 (central cortex: sensory and motor function), T7 & T8 (temporal cortex: processing of language and sounds), P3 & P4 (parietal cortex: perception, multisensory integration), and O1 & O2 (occipital cortex: visual processing). Odd number stands for the left brain, while even number represents the right brain. For musicians in the left panel, the information flows that are significant in strict mode (red links) are $F3 \rightarrow [O1, C3, C4, T8]$, $[F4, C3] \rightarrow T7$, $P4 \rightarrow [C3, T8, O2]$, while the information flows that are significant in “let-go” mode (green links) are $F4 \rightarrow O1$, $P4 \rightarrow T7$. For listeners on the right panel, the information flows that are significant in strict mode are $P3 \rightarrow [T7, F3]$, $T8 \rightarrow T7$, $C4 \rightarrow F4$, whilst the information flows that are significant in “let-go” mode are $[F3, F4] \rightarrow [C4, T8]$, $C3 \rightarrow T7 \rightarrow C4$. The differences between strict mode and “let-go” mode lie in the difference of locations of sink and sources activities and the directions of information flows.

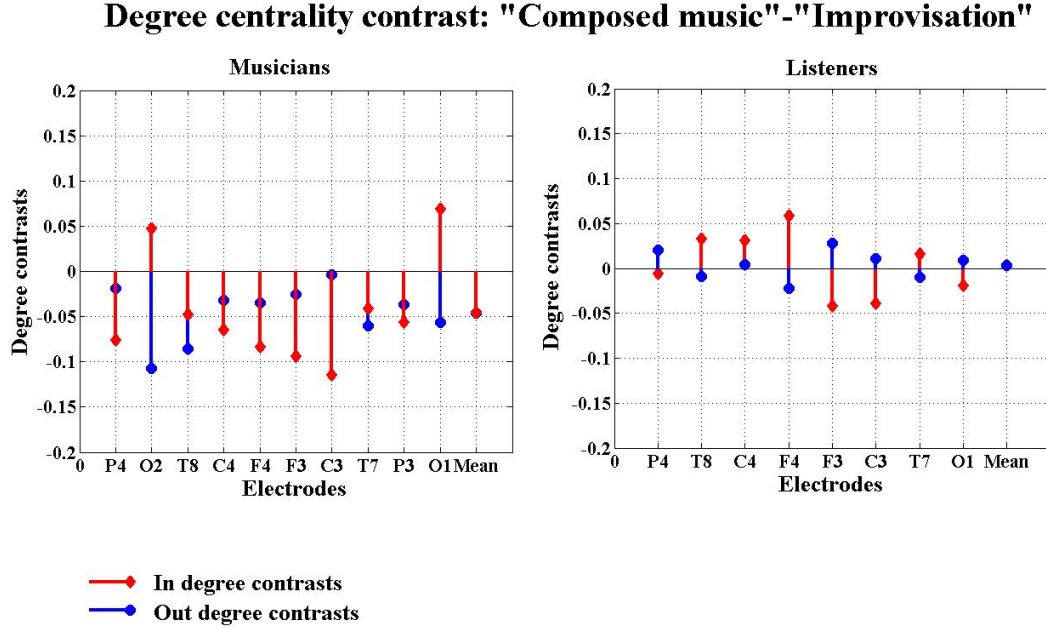


Figure 6. Degree centrality contrasts between composed music and improvisation in the second experiment. In this figure, we plot the contrasts of in (red stems) and out (blue stems) degree centralities between composed music and improvisation. The left panel is for musicians, while the right panel is for listeners. Since one of the listeners has only 8 electrodes, thus we use the 8 common electrodes: P4, T8, C4, F4, F3, C3, T7, P3 for all listeners. The x-axis labels the electrodes and the overall mean degrees for all electrodes, while the y-axis displays the normalised degree centralities. We see that musicians and listeners have opposite signs (negative for musicians and positive for listeners) for the degrees contrasts between composed music and improvisation. This implies that musicians have higher level of integraty between large brain regions during improvisation than during composed music, which are opposite for listeners.

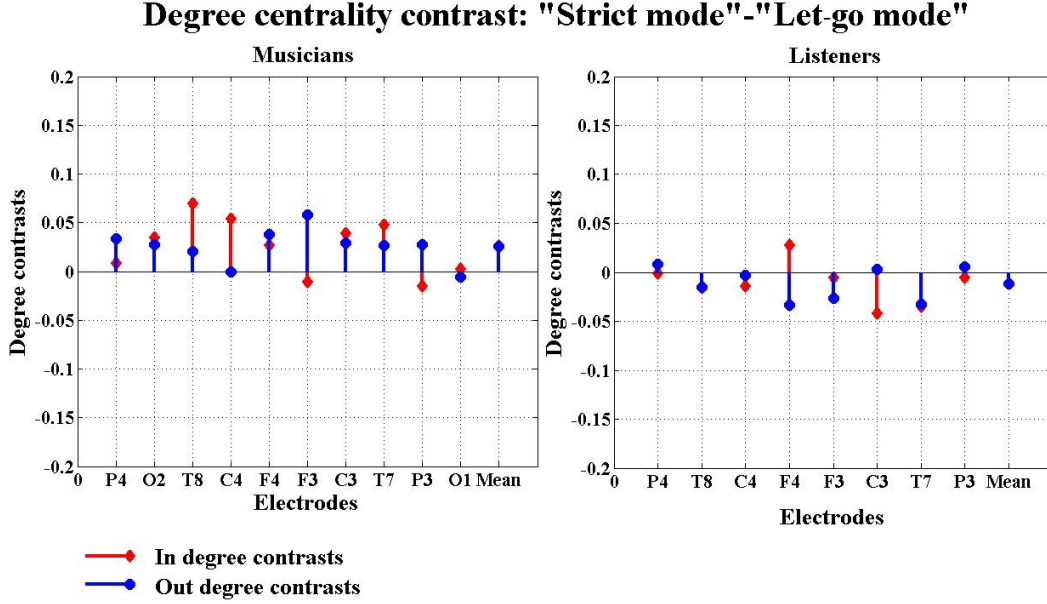


Figure 7. Degree centrality contrasts between strict mode and “let-go” mode in the second experiment. In this figure, we plot the contrasts of in (red stems) and out (blue stems) degree centralities between strict mode and “let-go” mode against electrodes. The left panel is for musicians, while the right panel is for listeners. Since one of the listeners has only 8 electrodes, thus we use the 8 common electrodes: P4, T8, C4, F4, F3, C3, T7, P3 for all listeners. The x-axis labels the electrodes and the overall mean degrees for all electrodes, while the y-axis displays the normalised degree centralities. We see that musicians and listeners have opposite signs (positive for musicians and negative for listeners) for the degrees contrasts between strict mode and “let-go” mode. This implies that musicians have higher level of integraty between large brain regions in strict mode than in “let-go” mode, which are opposite for listeners.

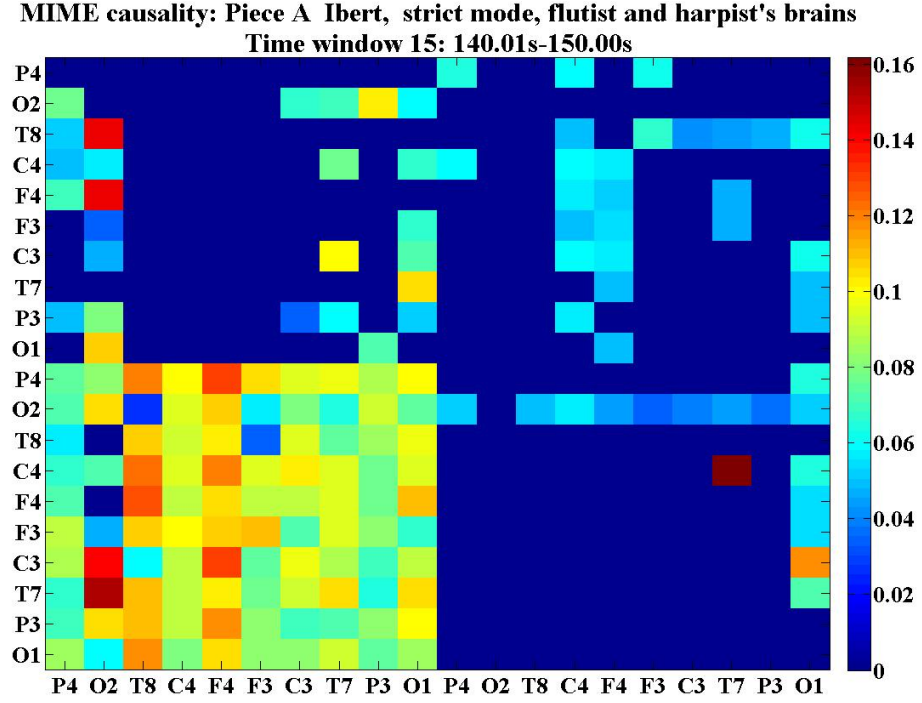


Figure 8. Colour-map of cross-brain causality matrix between flutist and harpist in the second experiment. This colour-map (scaled between 0 and 1) was taken for MIME cross-brain causalities between flutist and harpist in piece A: Ibert (strict mode) at time window 15 (140.01s-150.00s). This matrix plot has 20×20 lattices which can be divided into four 10×10 blocks, i.e. the two diagonal blocks (upper-left and lower-right) and the two off-diagonal block. The diagonal blocks are for intra-brain causalities, while the off-diagonal blocks are for cross-brain causalities. In this figure, the lower-left block is brighter than the upper-right block, which indicates that it is stronger in causalities for harpist \rightarrow flutist than for flutist \rightarrow harpist.

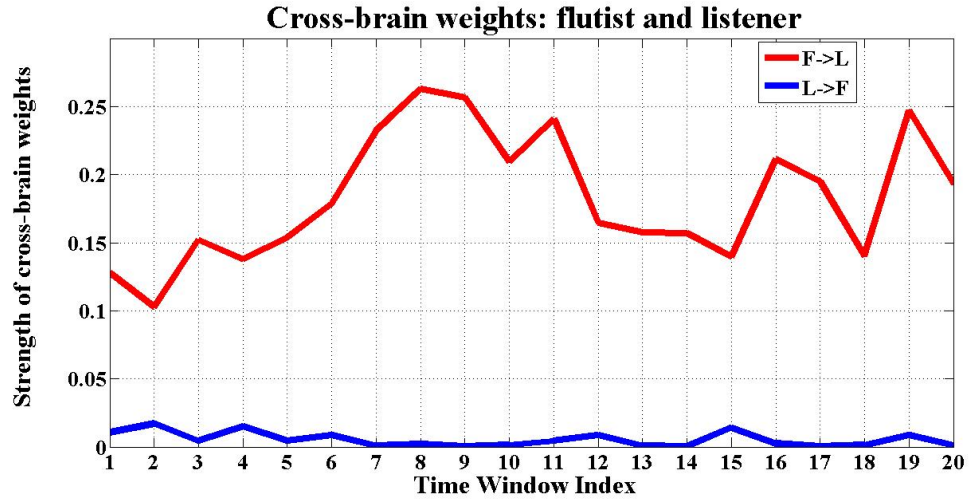


Figure 9. The cross-brain weights between flutist and listener in the second experiment. This figure plots the average cross-brain causalities between flutist and listener against time windows, for the performance in piece A: Ibert, strict mode. The red curve stands for the flutist→listener, while the blue curve represents listener→flutist. This graph indicates that the interaction between flutist and listener is dominated by the direction from flutist→listener, in which the average causalities from listener→flutist are almost vanished, thus implies little causality from listener→flutist.